

Vegetation response to climate conditions based on NDVI simulations using stepwise cluster analysis for the Three-River Headwaters region of China

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ABSTRACT

Located in the hinterland of the Qinghai-Tibet Plateau, the Three-River Headwaters region (THR) features unique eco-environmental conditions and fragile ecosystems, which are very vulnerable to climate change. To investigate the impacts of varying climate conditions, the Normalized Difference Vegetation Index (NDVI) was employed as an indicator to reflect the response of the vegetation dynamics. A series of pixel based Vegetation Dynamics Stepwise-cluster Prediction models (VEDSP) were proposed to establish the relations between NDVI and climate conditions through using the data series of remotely sensed precipitation and temperature. The obtained simulation results for training and testing showed very good agreements with the monthly NDVI observations. Rather than air temperature, the precipitation was identified as the critical climatic factor to result in various NDVI values, especially the 2-month consecutive average precipitation. The developed VEDSP models were further applied to predict the temporal and spatial distributions of NDVI values for five future years (2020, 2040, 2060, 2080 and 2100) according to climate projections of Euro-Mediterranean Center on Climate Change Climate Model (CMCC-CM) under the RCP4.5 scenario. The projected changes of NDVI indicated a slightly significant positive trend in annual average NDVI values, while the monthly peak values of NDVI for the entire THR would decrease by 5.34% in the future relative to the historical averages of the time period from 2000 to 2013. Distinct effects of precipitation and temperature on the response of NDVI were further demonstrated. Findings from this study would be used to help analyze the ecological effects of climate change and enhance the understanding of ecological changes in the future.

1. Introduction

Vegetation cover is one of the most important indices to evaluate the conditions of ecosystem (Wang et al., 2015) as its changes are closely related to livestock breeding, deforestation and desertification monitoring and anthropogenic activities (Purevdorj et al., 1998). However, how to effectively quantify long-term changes of land cover is still a dilemma in ecological studies and watershed management. As far as such issue is concerned, the Normalized Difference Vegetation Index (NDVI), which is derived from the difference between the reflectance ratio in the red band and the near-infrared band, was proved to be very efficient (Carlson and Ripley, 1997). Over the past decades, the relation between NDVI and vegetation cover has been well established theoretically and empirically (Pettorelli et al., 2005), and NDVI has been

widely used as an effective indicator to quantify the vegetation cover in many studies (Field et al., 1995; Prince and Goward, 1995; Schloss et al., 1999; Fang et al., 2001; Xin et al., 2008; Vlek et al., 2010; Le et al., 2016; Rafique et al., 2016). It is agreed that strategies for ecosystem protection in a region would result in little effects without analysis of an adequate spatial resolution or length of ecological records. With the release of increasingly accessible products of long-term and high resolution satellites datasets, it has become very convenient to conduct ecological studies from NDVI at both regional and global scales since the early 1990s (Fensholt and Proud, 2012; Jia et al., 2016). Therefore, the knowledge of vegetation dynamics based on NDVI would substantially help to support decision making in local development and planning.

Correlation between NDVI and climatic factors provides a very

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practical way to explore the corresponding response of ecosystems to climate change (Potter and Brooks, 1998). It is well acknowledged that the spatial distribution of NDVI is a function of climate conditions, such as precipitation and temperature, and many studies have been undertaken to explore the response of NDVI to variations in precipitation and temperature at regional and global scales (Rundquist, 1994; Braswell et al., 1997; Kaufmann et al., 2003; Liang et al., 2015; Tian et al., 2015). Among these studies, complex correlation coefficient and partial correlation coefficient from linear regression were commonly used to reveal the relation between NDVI and climatic factors due to the simplicity of the methodology (Fensholt et al., 2009). These investigations aimed at determining the correlation and lag-correlation between climatic factors and NDVI, and thus identifying the main driving factors that force the changes of an ecosystem. Owing to the complexity of ecosystems and the uncertainty of the mechanisms driving the vegetation dynamics under climate change (Piao et al., 2006), the commonly used methods mentioned above were not capable of revealing the complex non-linear relation in the process of vegetation dynamics (Peng et al., 2012). As such, the linear assumptions based regression models would no doubt lead to distinct conclusions as presented in previous studies. For these varying results, they might be attributed to such facts as different climate conditions of study areas, different land covers and climatic anomalies of the chosen years.

The Three-River Headwaters region (THR), also known as the “Chinese water tower”, is the source region of the Yangtze, Yellow, and Lancang Rivers and has been identified to be extremely sensitive to climate change (Liu et al., 2014). Many studies have focused on climate change, vegetation cover and ecological protection of this region (Liu et al., 2008; Xu et al., 2008; Fan et al., 2010; Li et al., 2011; Li et al., 2014; Liu et al., 2014; Cai et al., 2015), especially on the temporal and spatial distribution of NDVI values and the historical relation between climatic factors and NDVI. For example, a continuously decreasing trend of grassland was found in the THR based on the spatial characteristics of vegetation distribution in the late 1970s, early 1990s, and 2004 (Liu et al., 2008). Through using the residual analysis method and simple linear regression, Li et al. (2011) demonstrated that the contribution of climatic factors and human activities to vegetation growth were 79.3% and 20.7%, respectively. Liu et al. (2014) used linear regression analysis and Hurst exponent analysis to reveal an increasing trend in the spatial-temporal coverage of vegetation in the northern part of THR from 2000 to 2011 and a decreasing trend in the south, with a certain time lag in the response of vegetation coverage to precipitation and potential evapotranspiration. No matter that many interesting and significant findings were generalized based on the relation between NDVI and vegetation cover in the THR, it is noted that linear regression tools being applied would also result in high inaccuracy and uncertainties associated with the simulation and prediction. As a result, these obtained conclusions would be likely to be unreliable due to the limitations of the linear assumption. Thus, it is desired that more effective methods should be proposed to address the complex and non-linear relations between climatic factors and NDVI in such area as THR. Accordingly, the knowledge of vegetation dynamics in response to climate change would need to be further reflected and expanded.

Besides the linear regression, some studies applied the Dynamic Global Vegetation Model (DGVM) to simulate the vegetation distribution of the THR under climate change, such as the modified Lund-Potsdam-Jena Dynamic Global Vegetation Model (LPJ model) with climate projections to analyze the changing tendency of vegetation distribution in the Qinghai-Tibet Plateau (Gao et al., 2016). The LPJ model is a biogeochemistry process-based model with climatic factors (precipitation, temperature, cloud amount, etc.), soil texture and CO₂ concentration as inputs to obtain the potential evapotranspiration and soil temperature, and then, calculate the seasonal plants functional types (Sitch et al., 2003). The results showed that the NPP was projected to increase by 79% and 134% under the RCP4.5 and RCP8.5, respectively, but the parameters used were not altered with the change

of climate and vegetation conditions, which might reduce the accuracy of simulation.

As a potential approach to represent nonlinear relations between climatic factors and NDVI, stepwise cluster analysis (SCA) has the ability to capture the discrete and nonlinear relation between dependent and independent variables (Wang et al., 2013; Fan et al., 2015; Han et al., 2016). The SCA can clearly show the significance levels of different clustering branches, and hence the importance of different input indices can be presented (Sun et al., 2009). Based on the mono-variate automatic interaction detection algorithm, Huang (1992) firstly proposed SCA method to analyze urban air quality. This study captured discrete and nonlinear relations between explanatory, such as industrial coal consumption, population density, traffic flow and shopping density, and response variables, such as SO₂, NO_x and dust fall. Li et al. (2015) proposed a hydrological inference model using the SCA method, and applied it to daily streamflow forecasting. The results showed that the model performed reasonably in capturing different hydro-climate behaviors in dry, medium, and wet years. Although many models have been developed based on SCA to explore the nonlinear relations between dependent and independent variables in the environmental field, few studies focus on the application of SCA in investigating the correlation between climatic factors and NDVI, and predicting NDVI variations with the changing climate.

Thus, this study aims at developing an integrated model based on SCA to establish the relation between NDVI and climate conditions, which is used to reveal the vegetation dynamics through predicting the temporal and spatial distributions of NDVI values across the THR. In this paper, the principles of the proposed model and model structures based on SCA are firstly presented. Then, The model performance for the simulations of monthly NDVI values, projected temporal and spatial changes of NDVI under climate change scenario, and the response of vegetation dynamics to climate change are sequentially analyzed and discussed. Conclusions are summarized at last.

2. Study area

According to “Plans for the National Comprehensive Experimental Zone for Ecological Conservation at the ‘Three-River headwaters region’, Qinghai” issued by China in 2005, the THR is mainly located in the hinterland of the Qinghai-Tibet Plateau, lying between 31.53–37.10°N and 89.41–102.40°E (Fig. 1). It covers an area of 312,000 km², of which the source regions of the Yellow (above Tangnaihai Station), Yangtze (above Zhimenda Station) and Lancang rivers (above Changdu Station) account for 30.2%, 49.4% and 9.8% of the THR, respectively. The remaining part is the internal drainage area, where rivers disappear or flow into inland lakes. The annual average runoff of THR is 47.5×10^9 m³, consisting of 20.1, 12.4, and 15.0×10^9 m³ from the Yellow, Yangtze and Lancang Rivers, respectively (Zhang et al., 2011).

In accordance with the Qinghai-Tibet plateau, the THR bears a climate with a wet and warm summer and a cool and dry winter, mainly due to high elevation (3335–6564 m) and the influence of the Asian monsoon. From 1965 to 2004, the annual average precipitation was 445 mm, approximately 85% of which occurring between May to September, and the annual average temperature was -1.45 °C. Moreover, precipitation was found to decrease from east to west (Zhang et al., 2011). In addition to large spatial and temporal variations in precipitation and air temperature, the drought in this region was also found to become increasingly severe after 1990s with annual precipitation from 262 to 773 mm and annual evaporation ranging 730–1700 mm (Yi et al., 2011).

As shown in Fig. 2, there are large spatial variations in the monthly NDVI values across the region, while the vegetation types are mainly alpine grassland and alpine steppe (Hu et al., 2011). Generally, the THR could be further divided into three sub-regions: 1) the south-eastern sub-region with NDVI values from 0.3 to 0.5 is covered by evergreen

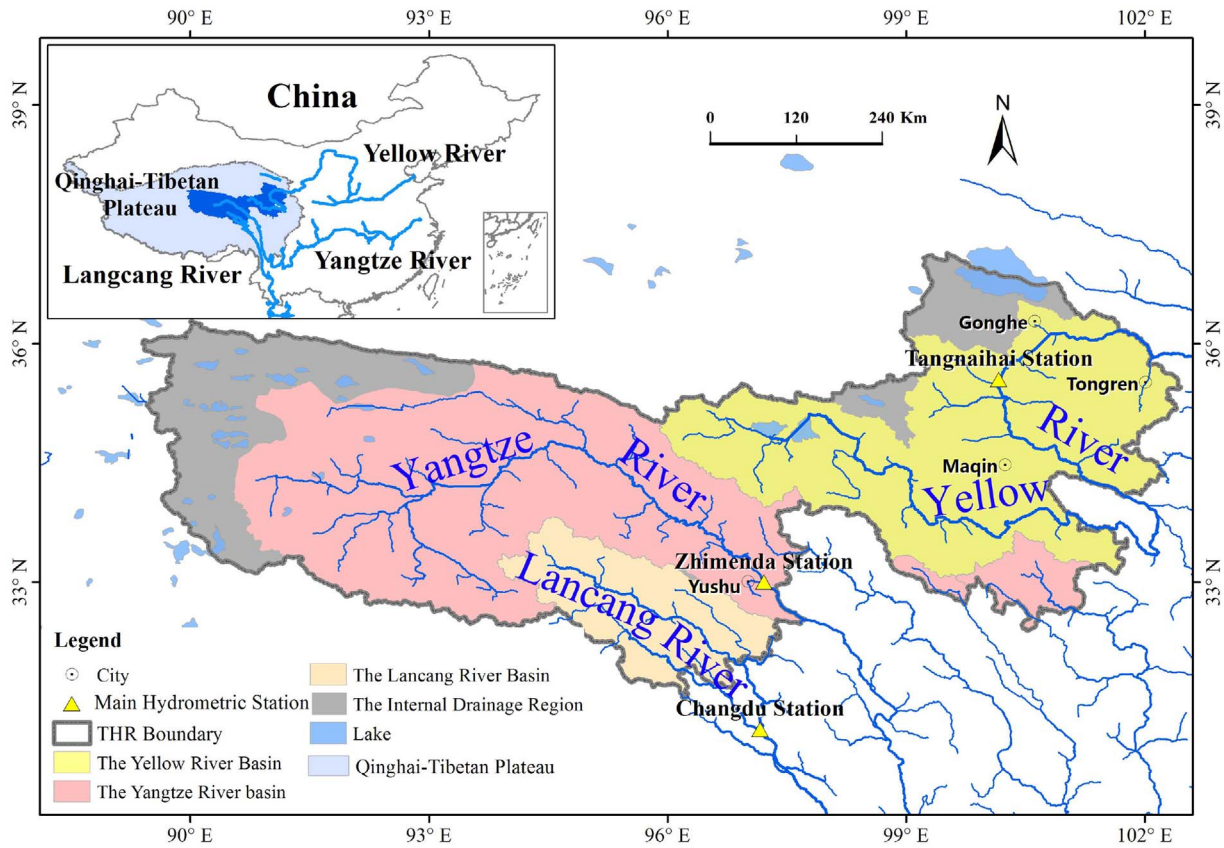


Fig. 1. Location of the Three-River headwaters region.

needle forest, broad leaved shrub and grasslands; 2) the land covers in the middle sub-region are mainly alpine meadow and alpine grasslands with NDVI values from 0.2 to 0.3, and 3) the sparsely vegetated lands in the north-western sub-region with NDVI values not greater than 0.2.

3. Methodology

3.1. Data sources and processing

All spatial datasets introduced in this study could be easily accessed on the internet, including land cover, remotely sensed precipitation, land surface temperature and NDVI. The land cover data set was collected from the Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences (<http://www.gscloud.cn>). The monthly CHIRPS (Climate Hazards Group Infrared Precipitation with Stations) precipitation products from 2000 through 2013 at 0.05° spatial resolution were acquired from the Climate Hazards Group (<http://chg.geog.ucsb.edu>) (Funk et al., 2014). Taking the computational efficiency and time consuming into consideration, the precipitation products were resampled to a 1° resolution by the spatial analysis tool, yielding a total of 38 pixels for the study area. As a result of the missing data (Aug. 2008–Dec. 2010) of pixels where Qinghai Lake were situated, the total number of pixels was reduced to 37. In order to reflect the impacts of climate conditions in previous months on the vegetation dynamics, such statistics of precipitation were also considered as the average amount of 2-month and 3-month consecutive precipitation. The monthly average temperature products (2000–2013) with a spatial resolution of 1 km were downloaded from the International Scientific & Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences (<http://www.gscloud.cn/>). As for the monthly precipitation, this product was further resampled to a 1° resolution, and the average values of 2-month and 3-month consecutive temperature were also calculated as

mentioned above.

The monthly GIMMS (Global Inventory Modelling and Mapping Studies) AVHRR (Advanced Very High Resolution Radiometer) NDVI datasets (2000–2013) have a spatial resolution of 8 km, and are collected from the NASA Earth Exchange (<https://nex.nasa.gov/nex/>). To avoid data noises from the clouds and aerosol, the Maximum Value Composite (MVC) method was applied to the datasets (Holben, 1986). The assumption of MVC is that the position of clouds is constantly changing, and thus the maximum NDVI value for each pixel was chosen as the value of pixels.

As far as future precipitation and temperature are concerned, the outputs of scenario (2006–2100) simulations of Euro-Mediterranean Center on Climate Change Climate Model (CMCC-CM) participating in the Coupled Model Intercomparison Project 5 (CMIP5) were adopted since this model has been operated at the finest spatial resolution of 0.75° (Palazzi et al., 2015). Note that future precipitation and temperature in this study was only analyzed for the representative concentration pathways 4.5 (RCP4.5) stabilization scenario, where the total radiative forcing is stabilized as 4.5 W/m² by 2100 (Clarke et al., 2007).

In view of the recognized overestimation of CMIP5 precipitation for each scenario in the Qinghai-Tibet Plateau (Su et al., 2013), a correction was applied to the amount of precipitation before the data were used as inputs to the model for predictions of NDVI values. During the same period (2006–2013), the monthly average precipitation from the CHIRPS datasets and CMCC-CM was compared to derive the coefficient of correction, using:

$$\hat{P} = P_{CMIP} \cdot \frac{\bar{P}_{CHIRPS}}{\bar{P}_{CMIP}} \quad (1)$$

where $\hat{P}$ is the corrected monthly precipitation relative to original CMCC-CM precipitation P_{CMIP} , $\bar{P}_{CMIP}$ and $\bar{P}_{CHIRPS}$ are the monthly average precipitation of CMCC-CM and CHIRPS, respectively. As

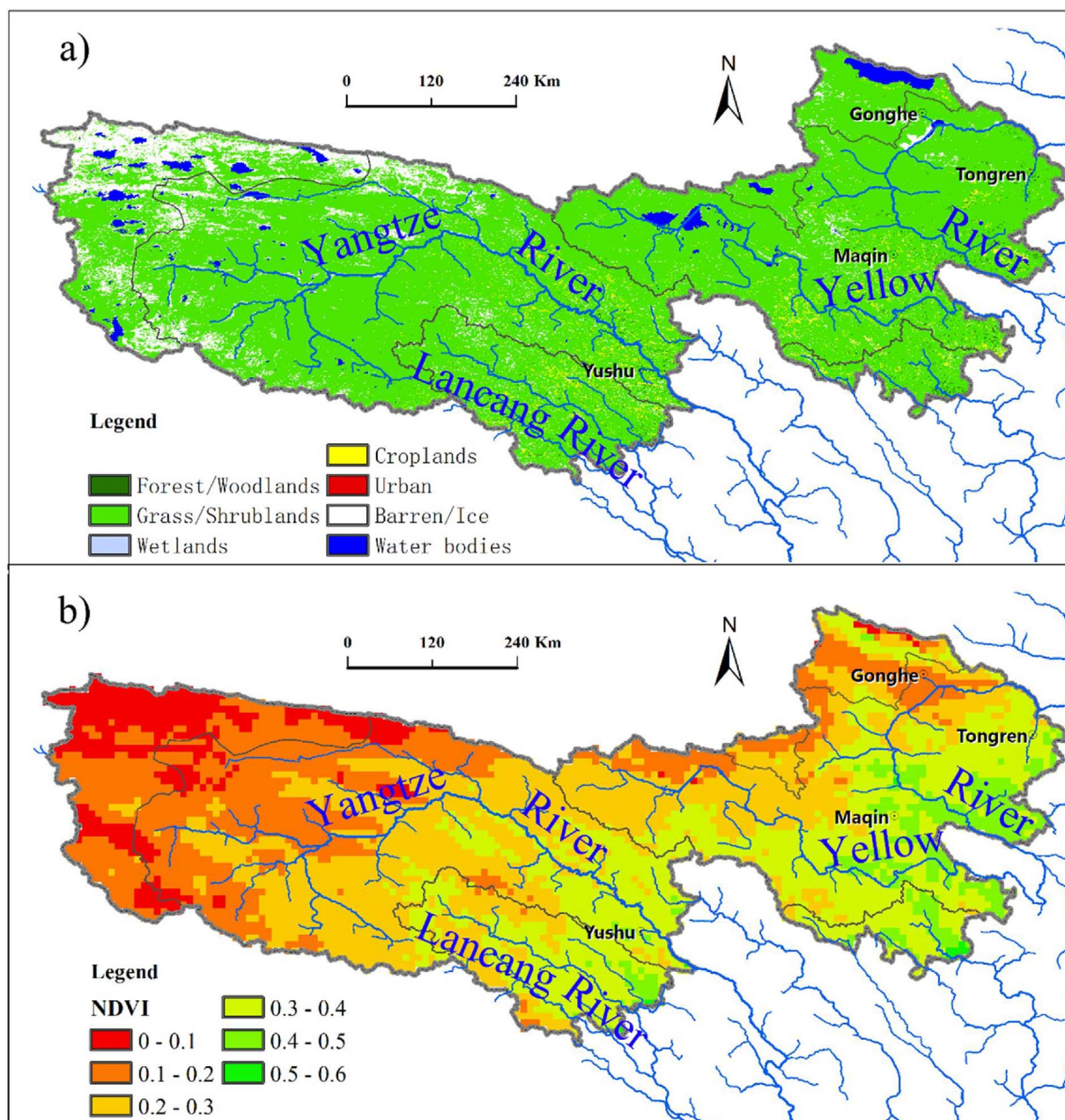


Fig. 2. Distribution of land cover and monthly average NDVI values across the THR in 2000.

depicted in Fig. 3, the monthly precipitation correction coefficients for the non-growing season (November–April) are higher than those for the growing season (May–October), especially for November and December. Similar conclusions were also found by Su et al. (2013) that the largest bias of precipitation among different Global Climate Models (GCMs) tended to occur in winter for all the periods and scenarios as a result of the uncertainties of the GCMs simulations. The correction made the modified CMIP5 precipitation data more comparable to the CHIRPS datasets (Fig. 4).

In order to make various predictors in the model have the same importance on the NDVI simulations, a linear normalization operation was additionally implemented on the temperature and precipitation as well as their statistics.

3.2. Model

To represent the relation between NDVI and various predictors, a

statistical inference model was proposed specifically for predicting vegetation dynamics in response to climate condition, i.e., the Vegetation Dynamics Stepwise-cluster Prediction Model (VEDSP). The VEDSP is an extended development of Stepwise Cluster Analysis (SCA) approach for statistical modeling simulation (Huang et al., 2006), the main principle of which is to build a cluster tree based on the probability level through continuous cutting and merging operation according to a given statistical criterion (Sun et al., 2009). Generally, there are two main sub-processes involved in the VEDSP, training and prediction.

3.2.1. Training

Two matrixes are first formed in the training process, predictor matrix $X_{a,m}$ and predictand matrix $Y_{a,n}$, respectively. The predictor matrix includes all the variables which have potential effects on the values of predictand (NDVI values). Moreover, Matrix $X_{a,m}$ and matrix $Y_{a,n}$ can be expressed as follows:

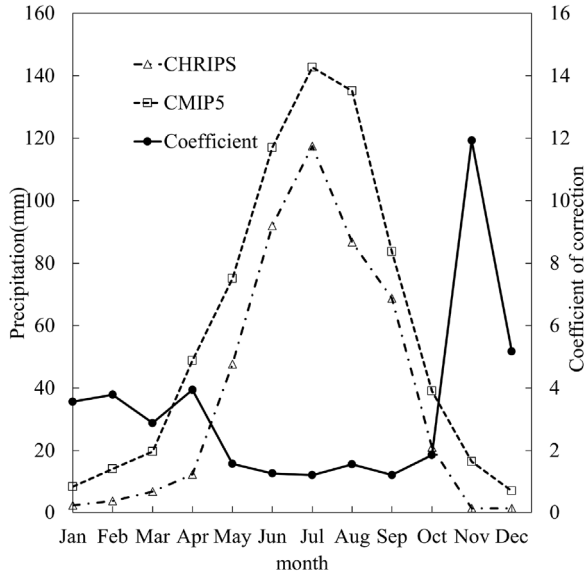


Fig. 3. Comparisons of monthly average precipitation between CHIRPS and CMIP5.

$$X_{\alpha,m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{\alpha 1} & x_{\alpha 2} & \cdots & x_{\alpha m} \end{bmatrix} \quad (2)$$

$$Y_{\alpha,n} = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{\alpha 1} & y_{\alpha 2} & \cdots & y_{\alpha n} \end{bmatrix} \quad (3)$$

where α is the number of samples; m and n are the number of variables in each sample.

The primary objective of the training process is to build a clustering tree which can be further used to perform predictions with new inputs associated with the predictors (Han et al., 2016). As a result, n cluster trees would be shaped corresponding to n predictands, and accordingly, each training matrix M_k is constructed as follows:

$$M_k = [X_{\alpha,m}, Y_{\alpha,n}] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} & y_{1n} \\ x_{21} & x_{22} & \cdots & x_{2m} & y_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{\alpha 1} & x_{\alpha 2} & \cdots & x_{\alpha m} & y_{\alpha n} \end{bmatrix} \quad (4)$$

where $k = 1, 2, 3, \dots, n$. When the VEDSP model is undertaken on each training matrix M_k , and α samples are then grouped into various clusters.

The F test based on Wilks' likelihood ratio is used as the criterion for

clustering. When the F test is satisfied, for example, cluster set M would be cut into two sub-clusters M_β and M_γ which contain β and γ samples ($\alpha = \beta + \gamma$), respectively. In order to cut a cluster set, it is fundamental to determine the optimal cutting point, which satisfies that the value of Wilks' statistic Λ is the minimum compared to any other cutting alternatives when the samples are sequenced according to the values of each predictor array (Wilks, 1963). In which, Λ can be calculated as:

$$\Lambda = \frac{|W|}{|T|} \quad (5)$$

where T and W are the total-sample sums of squares and cross products (SSCP) matrix $\{t_{ij}\}$ and the within groups SSCP matrix $\{w_{ij}\}$, respectively (Gatignon, 2014); $|T|$ and $|W|$ are the determinants of matrixes $\{t_{ij}\}$ and $\{w_{ij}\}$, respectively. The smaller the Λ -statistic is, the larger the difference between the means of M_β and M_γ is. When the value of Λ is large enough, therefore, clusters M_β and M_γ would be merged into a greater cluster instead of being cut. According to Rao's F -approximation (Huang, 1992), R -statistic can be expressed as:

$$R = \frac{1 - \Lambda^{1/s}}{\Lambda^{1/s}} \frac{ZS - P(K-1)/2 + 1}{P(K-1)} \approx F_{v_2=ZS-P(K-1)/2+1}^{v_1=P(K-1)} \quad (6)$$

$$Z = \alpha - 1 - (P + K)/2 \quad (7)$$

$$S = \sqrt{\frac{P^2(K-1)^2 - 4}{P^2 + (K-1)^2 - 5}} \quad (8)$$

where K is the number of groups, P is the number of predictand. When $K = 2$ or 3 , or $P = 1$ or 2 , the R -statistic will reduce to an exact F -variante, and so we would have the following expression.

$$F_{\alpha-P-1}^P = \frac{1 - \Lambda}{\Lambda} \frac{\alpha - P - 1}{P} \quad (9)$$

As a result, the criterion of cutting and merging is transformed into making F tests (Huang, 1992). Consider cluster set M_α being cut into two sub-sets M_β and M_γ based on the value of x_{i^*,j^*} , and F -test would then be undertaken.

$$F(P, \beta - P - 1) = \frac{1 - \Lambda(\beta, \gamma)}{\Lambda(\beta, \gamma)} \frac{\beta - P - 1}{P} \quad (10)$$

If $F \geq F_1$ (F -value at a defined level of significance σ with the freedom of $\beta - P - 1$), cluster set M_α is then allowed to cut into M_β and M_γ . In the meanwhile, x_{i^*,j^*} would be identified as the cutting criteria, which significantly affects the resulting values of predictions. Otherwise, cutting operation is not undertaken, and another cluster would be tested for cutting until no cluster can be further cut. Following cutting operation, the next step is to test whether any of current sub-sets could be merged. For cluster sets M_ϕ and M_ψ , the F -value is calculated using:

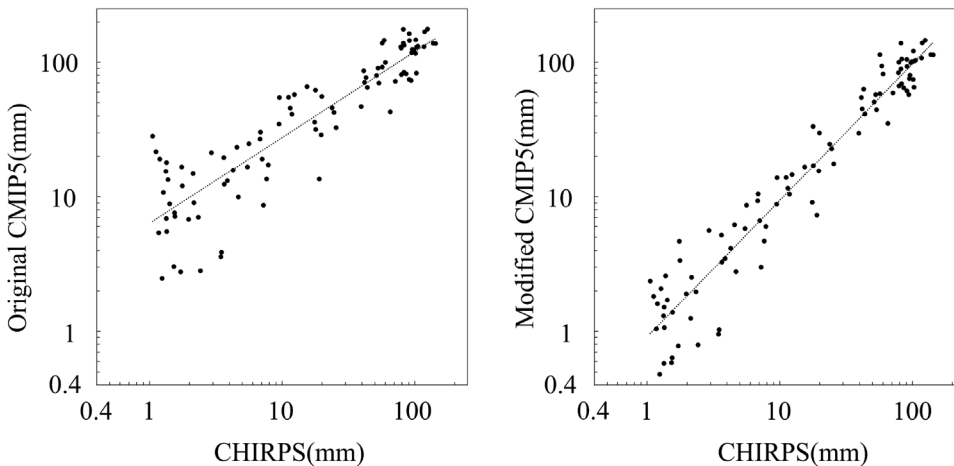


Fig. 4. Original and modified precipitation of CMIP5 against the remotely sensed precipitation of CHIRPS.

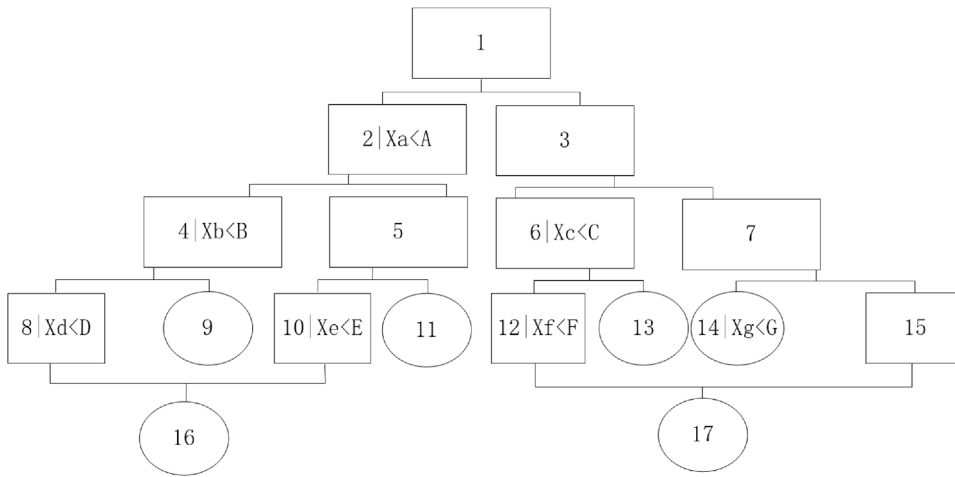


Fig. 5. The schematic drawing of a cluster tree (node | x-factor, criterion value).

Table 1
Predictors used in the model.

x factor	Predictor
X_1 - X_{37}	precipitation of current month
X_{38} - X_{75}	temperature of current month
X_{76} - X_{112}	2-month consecutive average precipitation
X_{113} - X_{150}	2-month consecutive average temperature
X_{151} - X_{187}	3-month consecutive average precipitation
X_{188} - X_{225}	3-month consecutive average temperature

where $y_k^{(\mu')}$ is the derived mean value of y_k in cluster μ' , and $R_k^{(\mu')}$ stands for the radius of y_k for tip cluster μ' and can be computed as:

$$y_k^{(\mu')} = \frac{1}{n_{\mu'}} \sum_{i=1}^{n_{\mu'}} y_{k,i}^{(\mu')} \quad \forall k \quad (13)$$

$$R_k^{(\mu')} = \left\{ \max_{i=1}^{n_{\mu'}} (y_{k,i}^{(\mu')}) - \min_{i=1}^{n_{\mu'}} (y_{k,i}^{(\mu')}) \right\} / 2 \quad \forall k \quad (14)$$

To simulate the variations of NDVI across the THR, many variables were selected as candidate input predictors for the VEDSP model based on the available data as mentioned above. As shown in Table 1, there are totally 225 predictors being simultaneously adopted to force the VEDSP model. It is noted that each predictor represents one variable at a pixel. In addition to monthly average precipitation and temperature, such climatic factors as 2- and 3-month consecutive average precipitation and temperature are also considered to reflect the lag effects of climate conditions on the vegetation dynamics.

A total of 37 pixels of precipitation data and 38 pixels of temperature data as well as 2-/3-month consecutive average values were generated for simulating NDVI changes of 200 pixels across the entire study area. Concerning the spatial distribution of NDVI values, the inputs for training are 200 matrixes, and hence, 200 cluster trees need to be shaped during the training process. Afterwards, the cluster trees would be used for prediction according to the new inputs associated with predictors, and the prediction of NDVI values would then be performed. To verify the reliability and usefulness of VEDSP, model prediction was preceded by a successful test after training.

In this study, there are 164 time series samples for each pixel, which are divided into two independent sets: 128 samples for training (from May 2000 to Dec. 2010), while the remaining 36 samples for model testing (from Jan. 2011 to Dec. 2013). Note that the values of two parameters should be assigned in advance before running the model. One is the level of significance of the F -test, and the other is the minimum number of samples for the end node. Generally, the significance level was set as 0.05, indicating that the criterion for cutting one a cluster or merging two clusters was $\sigma < 0.05$. The number of samples for each end node is required to be greater than two in order to satisfy the principles of statistics and to reduce the prediction uncertainty in this study.

4. Results

4.1. NDVI simulations for training & testing

With regards to each VEDSP model for each pixel, a resulting cluster tree was accordingly shaped during the training process. Through training the VEDSP model with inputs of 225 predictors against NDVI

$$F(P', \varphi + \phi - P' - 1) = \frac{1 - \Lambda(\varphi, \phi) (\varphi + \phi) - P' - 1}{\Lambda(\varphi, \phi) P'} \quad (11)$$

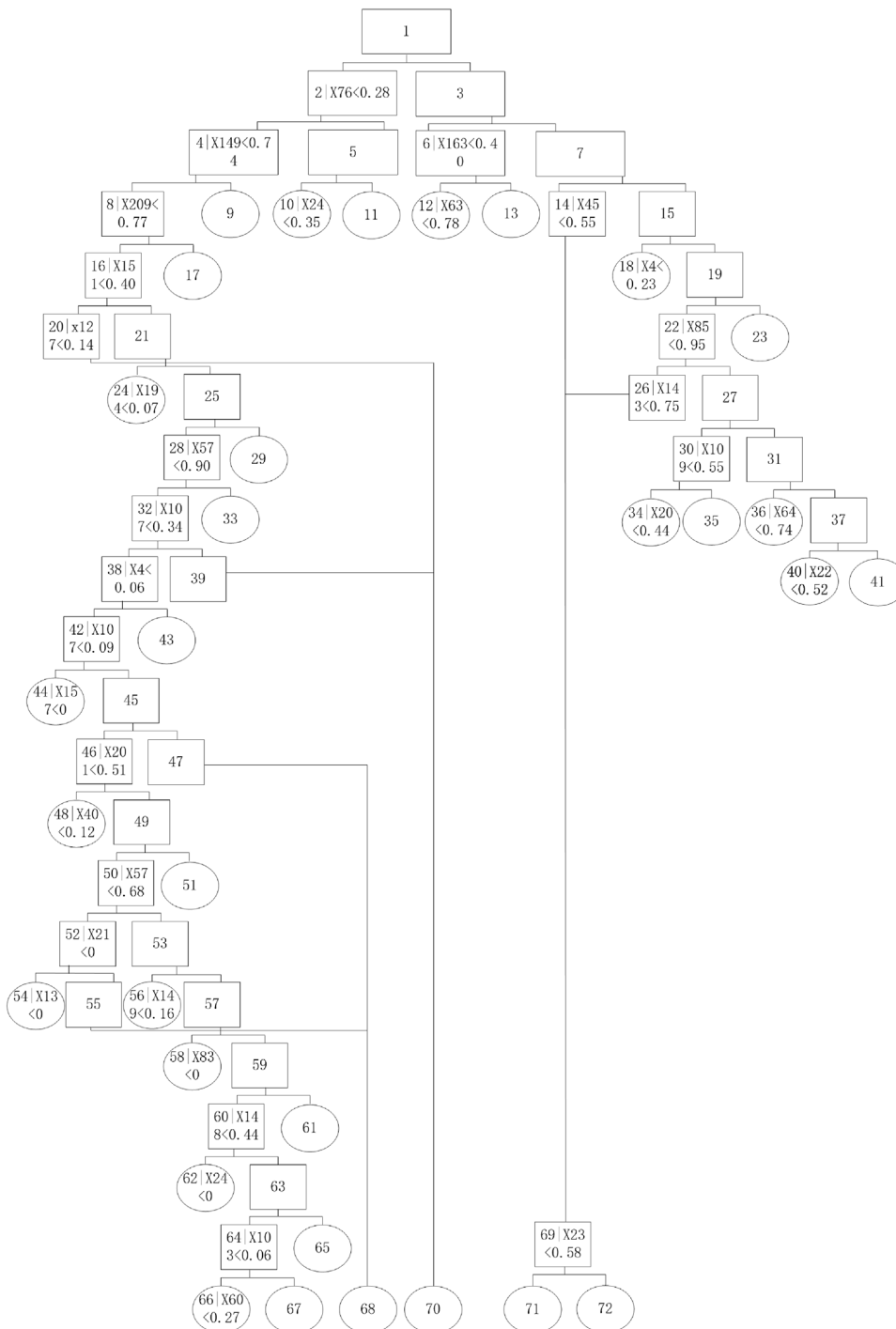
where φ and ϕ are the numbers of samples for set M_φ and M_ϕ , respectively. If $F < F_2$ (F -value at a level of $1-\sigma/2$ with the freedom of $\varphi + \phi + P' - 1$), cluster sets M_φ and M_ϕ would be then merged into a new cluster. Otherwise, no merging operation is performed, and the testing proceeds for other combinations of clusters until no clusters can be further merged. Based on the cut-merge loop, the training procedure is completed when all hypotheses of further cutting or merging are rejected. Thus, a cluster tree is obtained through the cutting and merging process, and the clustering group herein that cannot be cut or merged is called an end node. Fig. 5 is the schematic of a cluster tree. In which, $X_a, X_b, X_c, X_d, X_e, X_f$ and X_g are the factors in matrix $X_{\alpha,m}$, and A, B, C, D, E, F and G are criterion values. All the training samples were firstly combined as the initial node (Node #1) expressed as matrix M_k . Subsequently, these samples were classified into two sub-clusters through comparing the standardized value of $X_{i,a}$ ($i = 1, 2, 3, \dots, \alpha$) with A , which shows that the i th sample with $X_{i,a} < A$ would be grouped into cluster 2, otherwise into cluster 3. Then, following cutting and merging procedures progressed until convergence, and the sample cluster at each end node denoted as an ellipse (Node #16 for example) would be used for predicting.

3.2.2. Prediction

After the training is done, the derived cluster tree can be used for prediction, where the predictor values are used progressively as the criteria at each cutting node of the cluster tree. Each cutting node leads to two branches based on comparisons of x_{k,j^*} with x_{i^*,j^*} for predictor $\{x_{j^*}\}$ in the sample set of $\{x_k\}$. When a new sample is being input, consequently, the predictor values for this sample would help reach an end node along a cutting and merging route. The samples for each end node will be used to determine the values of predictand corresponding to new predictor sets. Let μ' be the tip cluster at an end node, the obtained predictand values can be expressed as:

$$y_k = y_k^{(\mu')} \pm R_k^{(\mu')} \quad (12)$$

Fig. 6. Cluster tree for NDVI simulations of pixel 17 (node | x-factor, criterion value).



time series for each pixel, a total of 200 models were ultimately established as well as 200 cluster trees for predicting the NDVI of the spatial pixels, which was numbered subsequently according to the direction from up to down and then left to right. Regarding the cutting point identified in the cut-merge loop, predictors selected as the cutting criterion would impose significant influences on the clustering of samples as well as the resulting values of predictand. The earlier the predictor is used as the cutting criteria, the more important the predictor seems to be in forcing changes of NDVI values. Therefore, vegetation dynamics might be more sensitive to changes of such predictors in the future.

Take the 17th pixel as an example, Fig. 6 illustrates the cluster tree for cutting and merging processes. As shown in Fig. 6, 34 times cutting

were implemented based on 26 predictors, such as X_{76} , X_{149} , X_{163} and X_{209} , and a total of 128 samples were ultimately grouped into 32 sub-clusters, which are presented as end nodes. No doubt the first cutting criteria based on X_{76} would play a decisive role in drawing a route to the end node. Thus, X_{76} can be regarded as the most significant predictor for the NDVI simulations of pixel 17.

Table 2 shows the occurrence times of predictors being identified as the first cutting criterion in 200 VEDSP models, and only predictors with occurrence times greater than 4 are listed. According to the count of various predictors, the NDVI simulations are mainly influenced by precipitation rather than temperature, especially such predictors as the 2- and 3-month consecutive average precipitation. Hence, there seems to be a prominent lag effect on the vegetation dynamics imposed by

Table 2
Occurrence times of predictors being used as the first cutting criteria.

Label	Count	Predictor
X ₇₆	47	2-month consecutive average precipitation
X ₁₅₄	25	3-month consecutive average precipitation
X ₈₄	24	2-month consecutive average precipitation
X ₁	17	precipitation of current month
X ₉₁	12	2-month consecutive average precipitation
X ₁₀₇	8	2-month consecutive average precipitation
X ₈₃	7	2-month consecutive average precipitation
X ₈₉	7	2-month consecutive average precipitation
X ₂₁	5	precipitation of current month
X ₉₃	5	2-month consecutive average precipitation
X ₁₆₂	5	3-month consecutive average precipitation
Others	38	

monthly precipitation. Besides, it can be observed that the NDVI values of almost all the pixels are mostly subject to precipitation at other pixels, implying remarkable impacts of spatial variations in climatic factors on the vegetation cover.

Fig. 7 illustrates the simulation results of NDVI over the entire THR for both training and testing against the remotely sensed observations. To evaluate the model performance of VEDSP, two metrics were applied, i.e., the coefficients of determination (R^2 from 0.0 to 1.0), and the Nash-Sutcliffe efficiency coefficients (NSE from minus infinity to 1.0). Both R^2 and NSE with a higher value indicate a more satisfying model performance (Nash and Sutcliffe, 1970). The deviations of NDVI simulations against observations (DV) were also calculated to assess the “goodness of fit” of simulations.

Generally, the results show a good match between simulations and observations for both training and testing period. As shown in Fig. 7, the values of R^2 for training and testing are 0.99 and 0.93, respectively. Correspondingly, the obtained NSE values are 0.99 and 0.93, respectively. In addition, the DV values are -0.01% and -1.30% , suggesting that very good simulations could be produced through VEDSP. Since the value of NSE is very sensitive to the extreme values (Legates and McCabe 1999), higher values of NSE would indicate the VEDSP is very capable of predicting the peak values of NDVI of the study area. Higher values of R^2 together with the values of DV approaching 0% further demonstrated the capability of VEDSP in representing the relations between NDVI and various climatic factors (Peterson and Hamlett, 1998).

As far as each pixel is concerned, the obtained values of R^2 for the testing period are presented in Fig. 8. The NDVI simulations for several pixels are found to be unsatisfactory according to low R^2 values. Specifically, there are two pixels with R^2 values lower than 0.5, and this may be attributed to major proportions of these pixels being occupied

by non-vegetation land cover. However, 88% of all the pixels have R^2 values greater than 0.8, demonstrating that the VEDSP model would be able to accurately predict the temporal and spatial distributions of NDVI values in the THR. In addition, it is noted that most of the pixels with R^2 below 0.8 are mainly located in the internal drainage region (Fig. 1), in which the NVDI value is relatively low (Fig. 2b).

4.2. Projected changes of NDVI under climate change

Through incorporating the projected climate scenario of RCP4.5 based on the CMCC-CM model, the VEDSP model was used to predict the changes of NDVI values in response to climate conditions in the future. As presented in Fig. 9, five representative years, i.e., 2020, 2040, 2060, 2080 and 2100 were selected to examine the spatial distributions of monthly NDVI values. Compared with 2001–2013, the monthly NDVI values for the future years exhibit distinct changing tendencies within one year. Generally, the monthly NDVI values during November through May become greater than the average value of 2001–2013. By contrast, a decrease of the NDVI peak values occurs in July or August. The average peak value of the five representative years decrease by 5.34% relative to that of 2000–2013.

Fig. 10 shows the annual average NDVI values of the entire THR for five future years in comparison with the NDVI time series from 2001 to 2013. The annual average NDVI value is found to increase by -1.00% , 3.57% , 4.57% , 7.19% and 4.96% for the year of 2020, 2040, 2060, 2080 and 2100 compared to the average value during 2000–2013 (0.246), respectively.

Fig. 11 shows the spatial distributions of NDVI values during the growing season in the future. According to the results, negligible changes can be found among the distribution of NDVI values in the future. The spatial pattern of NDVI in the future show no apparent differentiation compared with that in 2000.

Table 3 gives the projected changes of NDVI values at four distinct areas of the THR for the growing season and the whole year. According to the obtained results, it can be found that all the distinct areas would experience an increase in annual average NDVI values except for the year of 2020, which is consistent with the results shown in Fig. 10b. In addition, a general decrease in NDVI values for both the growing season and whole year in 2020 should be noticed.

5. Discussions

5.1. Trend analysis of projected NDVI

Since the establishment of “Qinghai Three-River Headwaters Nature Reserve”, human disturbances to vegetation cover in the THR have been strictly limited. Consequently, climate change would be the main

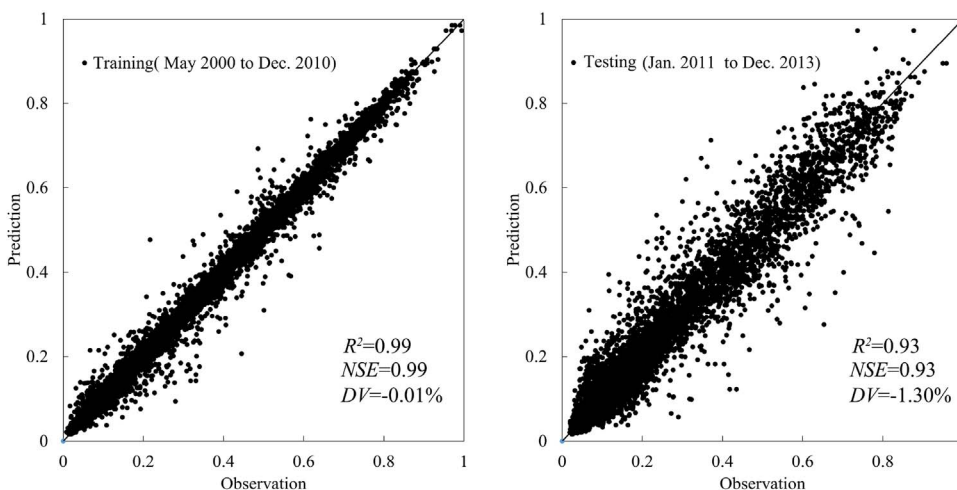


Fig. 7. Simulations against observations of NDVI values from May, 2000 to Dec. 2013.

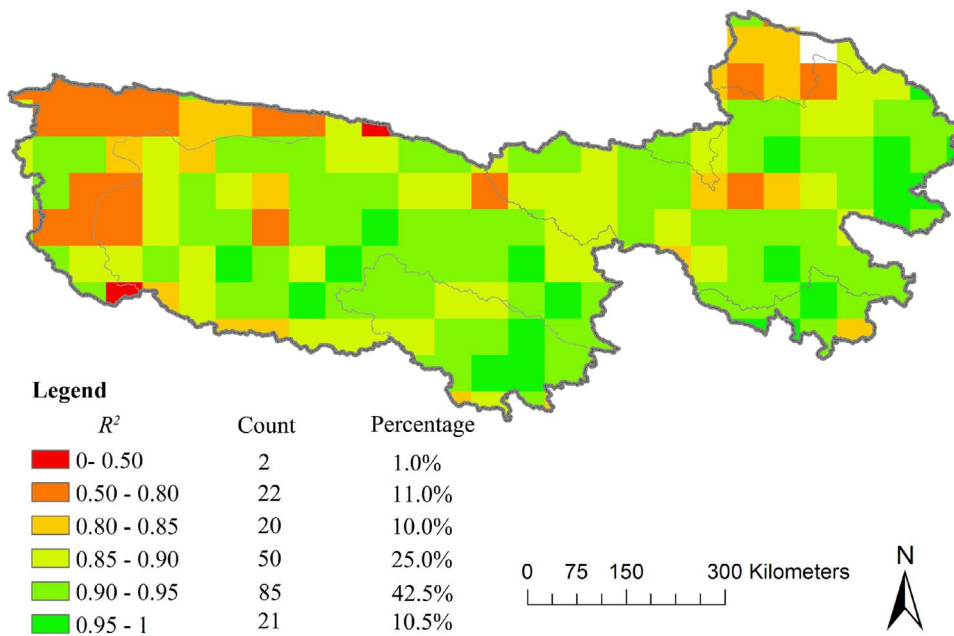
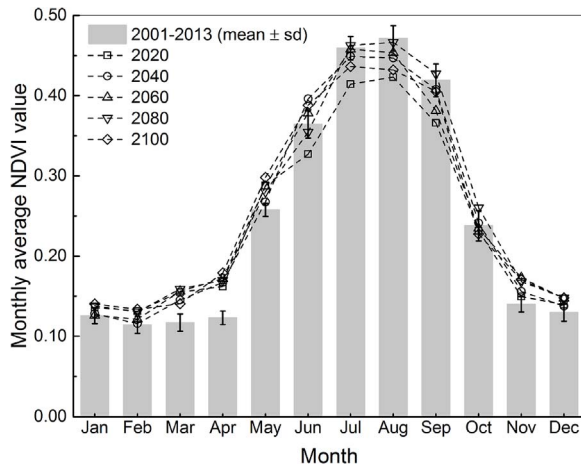
Fig. 8. The distribution of R^2 for the testing period.

Fig. 9. Monthly average values of NDVI for historic years (2001–2013) and projected years (2020, 2040, 2060, 2080 and 2100).

reason for changes of the distribution of NDVI values across the THR. Thus precipitation and temperature could be assumed as the dominant driving factors. According to the results of the trend analysis based on

the linear regression model, no obviously positive or negative trend could be detected in annual NDVI time series during 2001–2013 ($P > 0.05$). Although no trend was detected for 2020–2100 at a significance level of 0.05, it is interesting that a slightly increasing trend existed in the annual NDVI values in the future ($P < 0.1$). As a consequence, the projected climate conditions under RCP4.5 scenarios in the future would favor the vegetation cover in the THR. However, it should be noted that the increasing slope was so small, and such increase is mainly contributed by the vegetation during non-growing seasons.

5.2. Analysis of vegetation dynamics' response to climate conditions

As presented above, the precipitation was found to be the main climatic factor in VEDSP modeling to drive the changes of NDVI values as well as vegetation dynamics in the THR, especially the 2-month consecutive average precipitation (Table 2). Previous studies concluded that the THR would experience a higher temperature and little increase in precipitation in the future (Xu and Xu, 2012; Su et al., 2013; Gao et al., 2016). In this study, similar results would also be generalized under the projected changes of RCP4.5 scenarios that the precipitation varies little in the next 100 years. As shown in Table 4, no significant trend in the precipitation was generalized, although the amount of

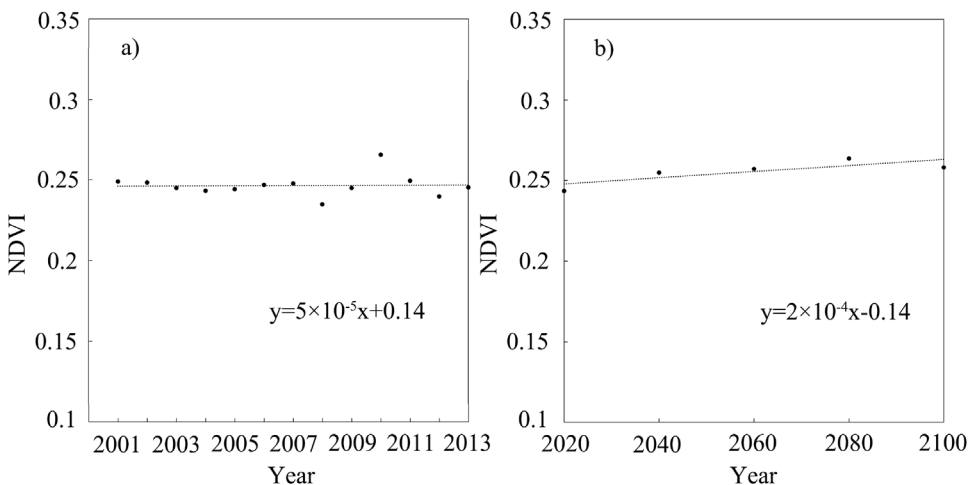


Fig. 10. Comparisons of annual average values of NDVI for the future years (2020, 2040, 2060, 2080 and 2100) with those for 2001–2013.

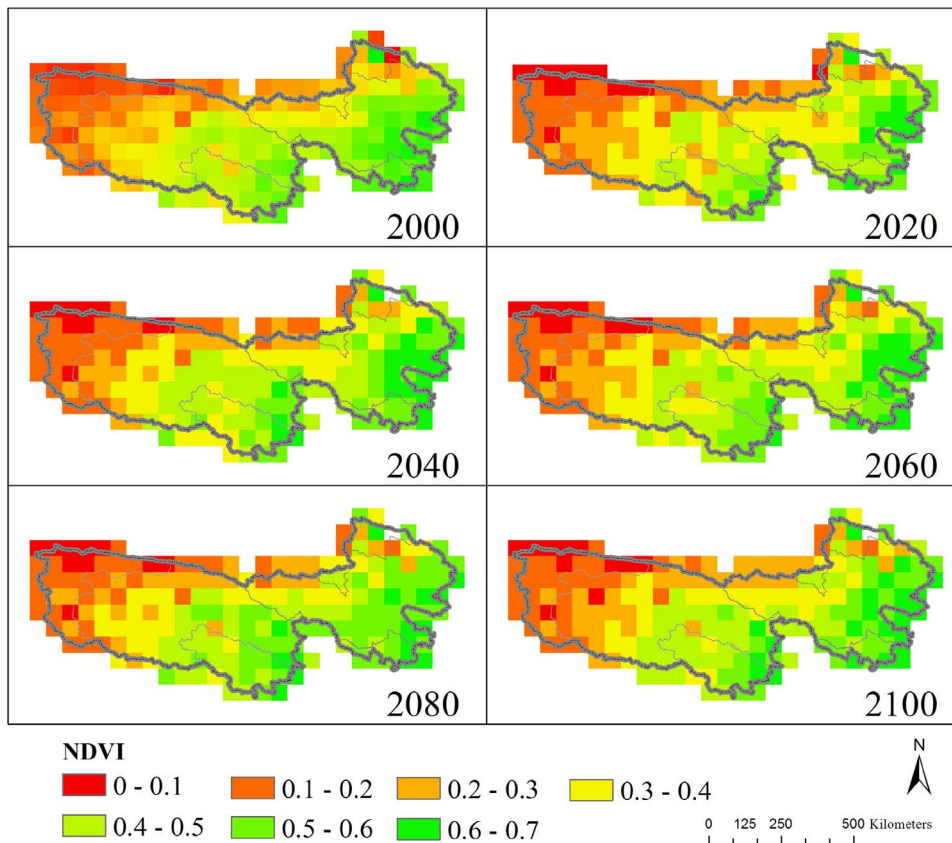


Fig. 11. Spatial distribution of NDVI values during growing season for 2000, 2020, 2040, 2060, 2080 and 2100.

precipitation would vary between -16.61% and 3.79% relative to the annual average value among 2001–2013. Nevertheless, dramatic reduction of precipitation relative to 2001–2013 was found to mainly account for the decrease of NDVI values in the drought years such as 2020. As for the tendency in the future, the changes of precipitation of 2040, 2060, 2080 and 2100 relative to 2020 are 24.5% , 23.1% , 22.9% and 9.64% , respectively. The changes of NDVI values relative to 2020 are 4.62% , 5.63% , 8.28% and 6.02% , respectively. Therefore, the consistent changing tendency between NDVI and precipitation further indicated that increasing precipitation would favor positive changes of vegetation dynamics.

The active accumulated temperature is the sum of temperature equal or above the base temperature during a certain period, which is an important index for vegetation growth. The increase in temperature may improve the active accumulated temperature and extend the growing season, which is in favor of the vegetation growth. However,

Table 4
Changes of projected annual precipitation in the THR.

Year	Precipitation (mm)	Change (%)
2001–2013	468.15	N/A
2020	390.37	-16.61%
2040	485.88	3.79%
2060	480.43	2.62%
2080	479.83	2.49%
2100	428.02	-8.57%

the increase in temperature would enhance the photosynthesis which would in turn raise the need of vegetation for water (Zhou et al., 2003). Considering the slight changes of projected precipitation in the THR, the growth of vegetation may be inhabited due to the relative lack of water during the growth season, which would result in the decrease in

Table 3
Comparisons of NDVI values for the five future years with the average value for 2000–2013.

Year		Yangtze River		Yellow River		Lancang River		Internal Drainage Area	
		NDVI	Change	NDVI	Change	NDVI	Change	NDVI	Change
2000–2013	growing season	0.348	N/A	0.463	N/A	0.465	N/A	0.202	N/A
	annual average	0.237	N/A	0.306	N/A	0.317	N/A	0.143	N/A
2020	growing season	0.321	-7.76%	0.421	-9.07%	0.445	-4.30%	0.188	-6.93%
	annual average	0.229	-3.38%	0.298	-2.61%	0.316	-0.32%	0.138	-3.50%
2040	growing season	0.352	1.15%	0.454	-1.94%	0.473	1.72%	0.201	-0.50%
	annual average	0.243	2.53%	0.311	1.63%	0.331	4.42%	0.143	0.00%
2060	growing season	0.344	-1.15%	0.452	-2.38%	0.473	1.72%	0.199	-1.49%
	annual average	0.242	2.11%	0.315	2.94%	0.336	5.99%	0.144	0.70%
2080	growing season	0.36	3.45%	0.458	-1.08%	0.479	3.01%	0.21	3.96%
	annual average	0.252	6.33%	0.317	3.59%	0.346	9.15%	0.151	5.59%
2100	growing season	0.341	-2.01%	0.449	-3.02%	0.468	0.65%	0.201	-0.50%
	annual average	0.244	2.95%	0.309	0.98%	0.342	7.89%	0.147	2.80%

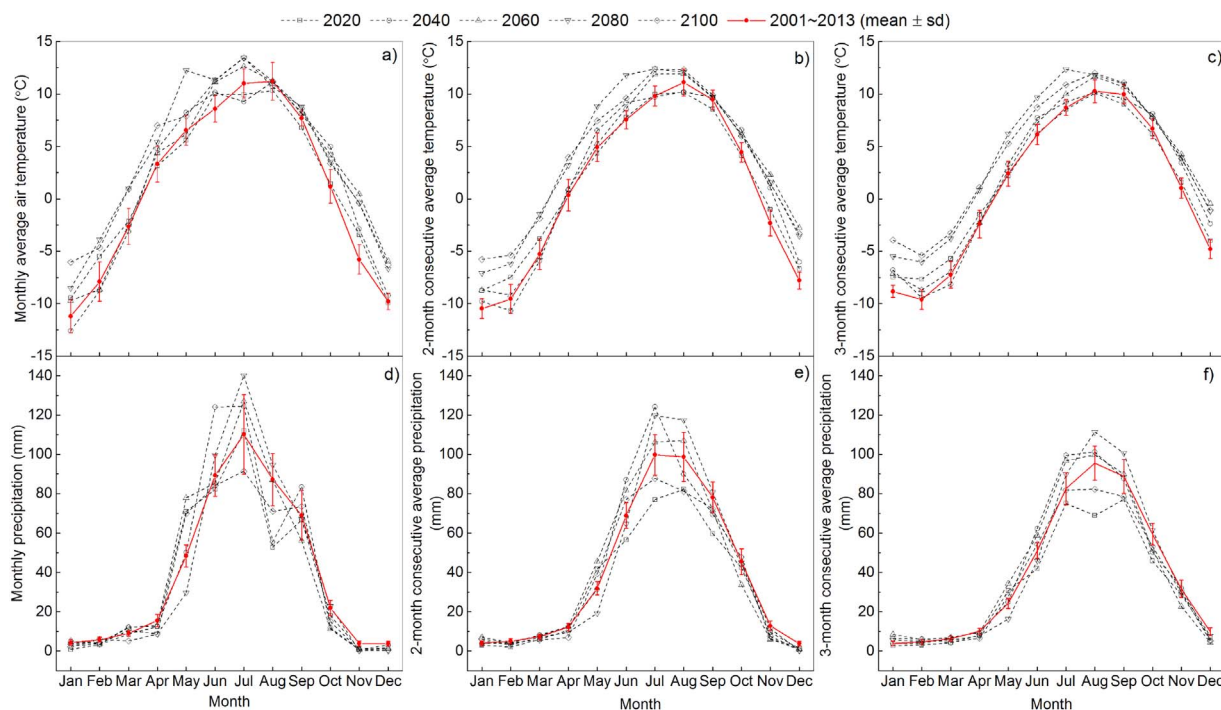


Fig. 12. Intra-annual variations in the predictors of temperature and precipitation: a) monthly average air temperature; b) 2-month consecutive average temperature; c) 3-month consecutive average temperature; d) monthly precipitation; e) 2-month consecutive average precipitation; f) 3-month consecutive average precipitation.

the peak values of NDVI as discussed above. From the intra-annual variations in the predictors of precipitation and temperature as illustrated in Fig. 12, an apparent increase in predictors of temperature would generally be found for almost all the months within the future year, but no consistent changes in predictors of precipitation could be concluded for each month in the future, especially during non-growing seasons. As such, the increase in annual NDVI values in response to climate change might be attributed to the positive effects of increasing temperature during non-growing seasons. Regardless of variations in precipitation during growing season, it cannot lead to significant increases of NDVI in the THR. Besides, increase of the air temperature would not contribute to vegetation growth without sufficient water. Thus, it would further suggest that increasing water demand for vegetation growth is likely to lead to the slight decrease in peak values of NDVI in the THR.

Although many results mentioned above seem to be inspiring, there are still some works needed to be undertaken in the future study. For example, the coupling effects of various land covers and climate conditions would be a crucial issue to be addressed. Other climatic factors should also be considered as the predictors in the model, such as atmospheric CO₂ concentration, sunlight duration, soil moisture etc. Ice and snow melt, caused by temperature increasing, changes the water supplement of vegetation, which may partly compensate for lack of precipitation and increase the soil moisture. Besides, the acknowledged uncertainty of GCMs would further make research necessary to introduce more models with high resolution as well as multiple scenarios.

6. Conclusion

This study developed a model based on stepwise-cluster analysis to predict the vegetation dynamics through representing the simulations of NDVI values. The proposed VEDSP models were further incorporated with the CMCC-CM climate projections under RCP4.5 scenario to forecast the temporal-spatial distribution of NDVI values in the THR for five future years (2020, 2040, 2060, 2080 and 2100). Some general conclusions have been drawn through this study as follows.

The VEDSP model was found to reflect the complex relations

between various climatic factors and NDVI effectively, and simulations for both calibration and testing demonstrated its capability of predicting the temporal-spatial distributions of monthly NDVI values in the THR. According to the established models, relative to air temperature, the precipitation was found to be the main climatic factor that would lead to various NDVI values in the THR. A prominent lag effect was identified in the response of NDVI values to precipitation, especially one month lag. In addition, the responses of NDVI values were not affected only by the local climate conditions, but the spatial variations in precipitation and temperature across the THR could also impose significant influence.

Climate change was found to impose slight impacts on the vegetation dynamics in the THR. The annual average values of NDVI presented a slightly increasing trend in the future, but the peak values of NDVI was found to decrease by almost 5.34% during the growing season in the future years. Distinct impacts of temperature and precipitation were found on the changes of NDVI in the THR. Although the precipitation is the driving factor to induce the variations in temporal and spatial distributions of NDVI values, it is mainly the increasing temperature during non-growing seasons that contributes to the increase in annual NDVI values. However, the significant increase in temperature during growing season would be likely to lead to negative effects on vegetation cover as it would also increase the water demand for vegetation growth. It was found that the decrease in peak values of NDVI can be attributed to the increasing temperature without sufficient water supply from precipitation. Moreover, similar results were also obtained in the source regions of the Yangtze, Yellow and Lancang River as well as the internal drainage area. Last but not the least, all the above conclusions coupling with the studies in-depth would be further utilized to help to make effective policies and conserving measures for ecological protection in the THR.

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